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R&D spillovers and firms' performance in Italy

Evidence from a flexible production function

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Abstract Using a translog production function we estimate the impact of R&D spillovers on the output performance of Italian manufacturing firms over the period 1998-2003. Technological flows are measured through an asymmetric similarity index that takes also into account the geographical proximity of firms. Results show that R&D spillovers positively affect firms production and that geography matters in determining the role of the external technology. Moreover, we find that the effect of R&D spillovers is high in the Centre-South of Italy and that the stock of R&D spillovers is Morishima complement to the stock of R&D own-capital.

Keywords R&D spillovers · Translog production function · Italian manufacturing firms

JEL Classification O33 · L29 · C23

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1 Introduction

The effects of R&D spillovers have been strongly emphasized in recent theoretical and empirical studies. The literature surveys by Griliches (1991), Breschi and Lissoni (2001) and Wieser (2005) identify many papers that found R&D spillovers to have a positive impact on production. However, the empirical literature is very scant as regarding the evaluation of the impact of R&D spillovers at firm level. The studies[1] using this level of data aggregation consider the stock of indirect R&D capital as an augmenting variable of a Cobb–Douglas production function and measure the external technology through other firms' stock of R&D capital.

This paper departs from previous literature on two points. Firstly, we use a flexible production function in the belief that the issues relating to technological transfers across firms may be properly understood using this specification rather than the Cobb–Douglas form. Indeed, the Cobb–Douglas is somewhat restrictive in that it requires the elasticity of substitution between factors to be unity. On the contrary, the translog is a generalization of the Cobb–Douglas and relaxing this restriction allows the understanding of whether external technology is complementary to or a substitute for private inputs (i.e., labour, physical, human and technological capital).

Secondly, we pay special attention to the measurement of R&D spillovers. If, on one hand, we follow the literature (see Griliches 1979) in determining the indirect stock of technological capital by the current and past investments in R&D made by other firms, on the other hand, we propose some refining procedures to model how, and to what extent, R&D capital spillovers flow across firms. We share with the literature the hypothesis that firms are not able to absorb all the external technology. As a consequence, we calculate the R&D spillovers as the weighted sum of the indirect stock R&D capital, but the method used to weight the innovation flows differs from that used by others in many aspects. Indeed, our weighting system for the external stock of R&D capital is based on the use of an index of similarity for each pair of firms. The hypothesis is that the more similar two firms are, the greater the flow of innovation between them (Jaffe 1986, 1988; Cincera 2005). As an index of similarity we use the uncentered correlation metric calculated by considering a set of firm-specific variables which defines the technological space.

Furthermore, we introduce two improvements with regards the micro-econometric applications of the index of similarity. As is known, the uncentered correlation metric yields a symmetric matrix of similarity. As the assumption of symmetry is restrictive, because direction matters in determining technological transfers from one firm to another, we propose the use of an asymmetric matrix of similarity. To this end, we proceed to transform the uncentered correlation metric by using the differences in human capital within each pair of firms. A further original element is related to geographical proximity as a key determinant of the flows of innovation. In theory, it is widely agreed that spatial agglomeration is positively correlated to the diffusion of technology (Marshall 1920; Jacobs 1969; Romer 1986; Arrow 1962; Koo 2005;

[1] Aiello and Pupo (2004), Aiello et al. (2005), Aiello and Cardamone (2005), Cincera (2005), Jaffe (1986), Jaffe (1988), Los and Verspagen (2000), Medda and Piga (2004), Raut (1995), Wakelin (2001).

Audretsch and Feldman 2004). However, it is worth noting that, in Italy, the spatial dimension of the flow of knowledge has been disregarded by all the existing papers analysing the impact of R&D spillovers. Therefore, we attempt to fill this gap and test the hypothesis that the closer two firms are, the more they will benefit each other' R&D. This is done through a spatial weighting scheme based on the great circle distance.

The empirical analysis is conducted on a panel of 1,203 manufacturing firms for the period 1998–2003. Data are obtained from the eighth and ninth "Indagine sulle imprese manifatturiere" (Survey of Manufacturing Companies) by Capitalia (2002, 2005). In the econometric setting, we refer to a system of equations derived from the translog production function (Christensen et al. 1973) and control for selection bias that zero values in R&D investments pose when the production function is log-linearized. This is done by modelling the decision to invest, or not, in R&D and then by estimating the production function with the 3SLS estimator.

The paper arrives at a number of interesting results on the impact of R&D spillovers on Italian firms' performance. Our evidence reveals that the contribution of R&D spillovers to firms' production is positive, whatever the weighting system of knowledge transmission and the sample of firms we analyse (full sample or sub-sample of firms according to their geographical localization), and higher than that estimated for the internal stock of R&D capital. Furthermore, it emerges that geographical proximity matters in determining the final result: our regressions which disregard geography in the process of technology diffusion underestimate the role of R&D spillovers. Finally, we find that the internal and external stocks of R&D capital are Morishima complements.

The remainder of the paper is organized as follows. Section 2 presents the production function specification and the estimation method adopted. Section 3 describes the procedures used to determine the R&D spillovers. Section 4 illustrates the data used, while Sect. 5 reports the econometric results. Section 6 concludes.

2 Empirical setting

2.1 Production function specification

This section describes the production function used to estimate the impact of technological spillovers on firms' production. Differently from the related literature, we consider a translog production function because of its higher flexibility with respect to the Cobb–Douglas specification. For the purpose of this paper, the trascendental logarithmic production function is expressed as follows:

$$\begin{aligned}\ln Y_{it} = {} & \alpha_i + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_{Ct} \ln CT_{it} + \alpha_{Sp} \ln Spill_{it} \\ & + \frac{1}{2}\beta_{LL}(\ln L_{it})^2 + \frac{1}{2}\beta_{KK}(\ln K_{it})^2 + \frac{1}{2}\beta_{CC}(\ln CT_{it})^2 \\ & + \frac{1}{2}\beta_{SpSp}(\ln Spill_{it})^2 + \beta_{LK} \ln L_{it} \ln K_{it} + \beta_{LC} \ln L_{it} \ln CT_{it} \\ & + \beta_{LSp} \ln L_{it} \ln Spill_{it} + \beta_{KC} \ln K_{it} \ln CT_{it} + \\ & + \beta_{KSp} \ln K_{it} \ln Spill_{it} + \beta_{CS_p} \ln CT_{it} \ln Spill_{it} + \varepsilon_{it} \end{aligned} \quad (1)$$

where Y is the output gauged by the value added, L indicates the number of employees, K denotes the physical capital measured by the book value of total assets, CT is the technological capital determined by applying the perpetual inventory method to R&D investments (depreciation rate is assumed to be 15%) and *Spill* is the stock of R&D spillovers every firm faces; subscript i refers to firms, t is time and ε is a white noise.

Following Berndt and Christensen (1973) and May and Denny (1979), we estimate the Eq. (1) together with a set of cost-share equations. This is because the resulting system of equations allows the using of additional information without increasing the number of parameters to be estimated (Antonioli et al. 2000). Furthermore, this procedure improves the efficiency of estimations and limits the multicollinearity bias in Eq. (1) (Feser 2004; Lall et al. 2001; Goel 2002).

The cost share equations are specified as follows. Denoting with S_L, S_K, S_{CT}, S_{SP} the cost shares of labour, physical capital, R&D capital and R&D spillovers, respectively, under the assumption of constant returns to scale,[2] we obtain:

$$S_{L,it} = \alpha_L + \beta_{LL} \ln L_{it} + \beta_{LK} \ln K_{it} + \beta_{LC} \ln CT_{it} + \beta_{LSp} \ln Spill_{it} + u_{L,it} \quad (2)$$

$$S_{K,it} = \alpha_K + \beta_{LK} \ln L_{it} + \beta_{KK} \ln K_{it} + \beta_{KC} \ln CT_{it} + \beta_{KSp} \ln Spill_{it} + u_{K,it} \quad (3)$$

$$S_{CT,it} = \alpha_C + \beta_{LC} \ln L_{it} + \beta_{KC} \ln K_{it} + \beta_{CC} \ln CT_{it} + \beta_{CSp} \ln Spill_{it} + u_{CT,it} \quad (4)$$

$$S_{SP,it} = \alpha_{Sp} + \beta_{LSp} \ln L_{it} + \beta_{KSp} \ln K_{it} + \beta_{CSp} \ln CT_{it} + \beta_{SpSp} \ln Spill_{it} + u_{Sp,it} \quad (5)$$

Since the sum of input cost shares must be equal to one, all the parameters have been estimated by considering the system composed by Eqs. (1), (2), (3) and (4). This choice allows us to solve the problems one would encounter in estimating Eq. (5). These difficulties are due to the fact that the costs of R&D spillovers are not observable (cfr note 9).[3]

2.2 Estimation method

There are two major econometric issues when estimating a production function like Eq. (1). The first issue is related to the endogeneity of regressors, whereas the second one regards the sample selection problem due to the log-linearization of the production function. We address these issues as follows.

The system of Eqs. (1–4) is estimated through the 3SLS estimator. We consider as instruments the 1-year lagged value of all the regressors of Eq. (1), except for lnSpill and lnSpill^2, which are assumed to be exogenously determined at firm level. The Hausman test supports this choice. Furthermore, the log-linearization of a production function creates a sample selection problem, arising from the fact that the stock of

[2] Constant returns to scale imply that $\sum_i \alpha_i = 1$ and $\sum_j \beta_{ij} = 0$.

[3] The labour cost share S_L is the total labour cost to the value added. Following Verspagen (1995), we compute S_K and S_C as $[P_I(\delta + r)]Z/Y$ where P_I is the investment price deflator, δ is the rate of depreciation assumed to be equal to 5% for physical capital and 15% for technological capital, r is the interest rate, which is assumed to be 5%, Z is the stock of capital (physical or technological) and Y is firms' output, measured as the value added.

R&D capital is constructed using R&D investments and that, in many cases, firms do not invest in R&D (zero-investment-values). Hence, we have a sub-sample of R&D performing firms (with positive values for R&D capital) and a sub-sample of non-R&D performing firms (with zero values for R&D capital), but the log-linearization of Eq. (1) restricts the sample to the R&D performing firms. In so doing, the log-linearization makes the sample no longer random, because it rules out the underlying process that leads each firm to invest, or not, in R&D. Consequently, there might be a selection problem due to the likely correlation between the decision to invest in R&D and the production function. As the selection occurs for the stock of R&D capital, which is a regressor, we address this issue using a treatment effect model and implementing a two-step instrumental variable procedure (Wooldridge 2002): in the first step we consider a probit model to explain the decision to invest in R&D, whereas, in the second step, we estimate the translog production function using as an instrument the fitted probabilities derived from the first step.

The dependent variable of the probit model is unity if the ith firm invests in R&D and is zero if it does not. The regressors are the explanatory variables of the production function (Eq. 1), plus the key determinants of innovative efforts that we select following the related literature (Leo 2003; Becker and Pain 2003; Gustavsson and Poldhal 2003; Bhattacharya and Bloch 2004).[4] From the probit model, we get the fitted probabilities ($\hat{G}_{it}$) that enter in Eq. (1) as an instrument. This procedure allows us to run the Eq. (1) for the R&D-performing firms only and is suitable for two main reasons. First of all, the usual standard errors and test statistics are asymptotically valid and, secondly, no particular specification of the probit model has to be set up, because of using the variable $\hat{G}_{it}$ as an instrument (Wooldridge 2002).[5]

3 The stock of R&D spillovers

If the external technology available to a firm is related to the R&D investments of other firms (Griliches 1979) then a first measure of R&D spillovers will be the unweighted sum of the R&D stocks of the other $n-1$ entities. This measure has two caveats: it assumes that (a) all the external technology is relevant for a firm and (b) the capacity to absorb technology does not differ across firms and sectors. In line with the argument that not all the investment efforts made by others are relevant for a firm (Griliches 1991), many papers agree that the measure of technological spillovers must

[4] The variables we consider as determinants of the decision to invest in R&D are the following: human capital, cash flow, investments in ICT, a dummy equal to unity if firm i exports and a set of dummies referring to the geographical location and the economic sector of each firm. The cash flow variable is computed as gross profits minus taxes plus depreciation. The ICT variable is the sum of hardware, software and telecommunication investments. Human capital is expressed by $\exp(\varphi_R Sh)$ where Sh is the average number of years of schooling (8 for primary and middle school, 13 for high school and 18 for bachelor degree) and φ_R is the regional rate of returns on education drawn from Ciccone (2004).

[5] Indicating with w the treatment indicator, which is equal to 1 if there is treatment and 0 otherwise, and with $G(x, z, \gamma^*)$ the probit specification, "what we need is that the linear projection of w onto $[x, G(x, z, \gamma^*)]$ actually depends on $G(x, z, \gamma^*)$, where we use γ^* to denote the plim of the maximum likelihood estimator when the model is mis-specified [...] These requirements are fairly weak when z is partially correlated with w" (Wooldridge, 2002, p. 624).

be a weighted sum of R&D capital stock of other firms. However, no consensus is achieved on the weighting system to be used. The most commonly used methods are based on either patents data (Jaffe 1986, 1988; Los and Verspagen 2000; Cincera 2005) or input-output matrices (Wakelin 2001; Medda and Piga 2004; Aiello and Pupo 2004; Aiello et al. 2005; Aiello and Cardamone 2005). Due to the fact that the I/O and the patent data are subject to criticism,[6] we propose the use of a weighting system of external R&D capital based on firms' technological similarity and/or geographical proximity.

3.1 Firms' technological similarity

The understanding of the firm's position in a technological space helps to determine its technological opportunities, that is the amount of technological resources available for each entity (Cohen and Levinthal 1990). Furthermore, technological opportunities affect the absorptive capacity to use new technology and to be innovative (Cohen and Levinthal 1989). Many authors (Jaffe 1986, 1988; Griliches 1979, 1991; Cincera 2005; Harhoff 2000; Inkmann and Pohlmeier 1995; Kaiser 2002) agree that absorptive capacity depends on technological proximity: the closer two firms are in the technological space, the more they benefit from each other's research efforts.

From an empirical perspective, the questions to deal with before measuring the similarity between firms regard the choice of the variables which define the technological space, and the index of similarity to be used. Several authors (Jaffe 1986, 1988; Los and Verspagen 2000; Cincera 2005) argue that patent data allow the proper definition of an innovative space, others use investments in R&D (Harhoff 2000; Adams and Jaffe 1996), while Inkmann and Pohlmeier (1995) consider a set of firm specific characteristics (size, demand expectations, industry affiliation). As for the calculation of firms' similarity, many studies (Jaffe 1986, 1988; Cincera 2005; Kaiser 2002; Los and Verspagen 2000) propose the uncentered correlation metric because, with respect to the Euclidian distance, this is not sensitive to the length of the vector which comprises the variables defining the technological space. We proceed by using the uncentered correlation metric which is expressed as follows:

$$\omega_{ijt} = \frac{\mathbf{X}_{it}\mathbf{X}'_{jt}}{\left(\left(\mathbf{X}_{it}\mathbf{X}'_{it}\right)\left(\mathbf{X}_{jt}\mathbf{X}'_{jt}\right)\right)^{1/2}} \tag{6}$$

[6] The use of patents to measure the flows of knowledge runs into the same problem encountered when patents are used as an indicator of firms' innovative activities, that is "not all inventions are patentable, not all inventions are patented" (Griliches, 1990, p. 1669). The I/O approach does not properly gauge the real magnitude of pure knowledge spillovers, as it is related to the flows of goods and services rather than to purely technological flows. Moreover, both I/O and patent matrices are generally available at industry level only and, consequently, their use at firm level (see, i.e., Los and Verspagen 2000; Aiello and Pupo 2004; Aiello et al. 2005; Medda and Piga 2004) requires that (a) the absorption of technology is constant across the firms in a sector (b) the extra-industry technology is the same for all firms belonging to the same industry.

where X is a set of variables defining the technological space of firms and t is time (1998–2003).[7] The index ω_{ijt} ranges from zero to one. It is zero when firm i and firm j are not related at all, while it is unity if the k-variables in X_{it} and X_{jt} are identical.[8]

Equation (6) yields a symmetric matrix of weights. This means that at time t the intensity of the technological flows from firm i to firm j is equal to that observed from firm j to firm i. This property of the index ω_{ijt} contrasts with the evidence that direction matters in determining how technology circulates from one firm to another. Therefore, we attempt to overcome the unrealistic assumption of symmetry by using the following transformation:

$$\begin{aligned}\hat{\omega}_{ijt} &= \frac{\mathbf{X}_{it}\mathbf{X}'_{jt}}{\left(\left(\mathbf{X}_{it}\mathbf{X}'_{it}\right)\left(\mathbf{X}_{jt}\mathbf{X}'_{jt}\right)\right)^{1/2}}\left[\frac{h_{it}}{\max(h_{it}, h_{jt})}\right] \\ \hat{\omega}_{jit} &= \frac{\mathbf{X}_{it}\mathbf{X}'_{jt}}{\left(\left(\mathbf{X}_{it}\mathbf{X}'_{it}\right)\left(\mathbf{X}_{jt}\mathbf{X}'_{jt}\right)\right)^{1/2}}\left[\frac{h_{jt}}{\max(h_{it}, h_{jt})}\right]\end{aligned} \tag{7}$$

where the variable h is a measure of human capital, as defined in note four. The idea to make the uncentered correlation asymmetric ($\hat{\omega}_{ijt} \neq \hat{\omega}_{jit}$) by using a measure of human capital relies on the fact that the firm's absorptive capacity is strongly dependent on the quality of its human capital [see, among many others, Lucas (1988), Vinding (2006) and Wang (2007)].

3.2 Firms' geographical proximity

It is commonly agreed that the flows of innovation depend not only on the technological but also on the geographical distance between firms: face-to-face contacts enhance knowledge spillovers whatever the technological similarity. Although a huge number of papers deals with the theoretical issues of the nexus between spatial agglomeration and knowledge spillovers (Marshall 1920; Jacobs 1969; Romer 1986; Arrow 1962; Koo 2005; Audretsch and Feldman 2004), the empirical analyses estimating the extent to which geography affects the diffusion of technology at firm level are very limited. The few exceptions are the studies by Adams and Jaffe (1996), Orlando (2000) and

[7] In the prevailing literature, the index of similarity is determined using only one variable (the investments in R&D or the sectoral patent data). This choice appears to be a strong constraint, because it is a very partial way of gauging the firm's capacity to absorb external technology (two firms may be similar in terms of R&D investments, but their "absorptive capacity" may be limited because of other factors, one of which might be, e.g., the availability of human capital). Moreover, our index of similarity differs at firm-pair level and this allows us to overcome the strict assumption that the firms operating in a given sector have the same absorptive capacity.

[8] The variables used to construct the index of similarity are the investments in ICT, the internal and external R&D investments, the ratio between the number of skilled workers and the number of unskilled workers (the skilled workers are those with at least a high school diploma) and the Herfindhal–Hirschmam index, as a measure of market concentration in the sector which the firm belongs to.

Lu et al. (2005). To the best of our knowledge no paper focuses on Italian manufacturing firms.

A way to weight the diffusion of innovation among firms located in different areas is to take into account the geographical distance between them. At this end we use the great circle formula, which yields the shortest distance between two points on a sphere. Within each pair of firms i and j, the distance between them (d_{ij}) is calculated by considering the distance between the administrative capital of the provinces where the firms operate. Given the distance (d_{ij}) between a pair of firms, an index of the geographical proximity is:

$$g_{ij} = 1 - \frac{d_{ij}}{\max(d_{ij})} \tag{8}$$

which is unity when $d_{ij} = 0$, namely when firms i and j are in the same province, and is zero when $d_{ij} = \max(d_{ij})$, that is when the distance between i and j equals the maximum distance, which, in Italy, is given by the distance from Aosta to Siracusa.

Finally, we attempt to merge the basic ideas beyond the Eqs. (7) and (8). In Eq. (7), we simply state that technological similarity is the only factor that explains the flow of innovation, while Eq. (3) attributes this uniqueness to geographical proximity. Since it is likely that the closer and more similar firms are, the more they benefit from each other's technology, we average the indexes $\hat{\omega}_{ijt}$ and g_{ij}:

$$\upsilon_{ijt} = \frac{\widehat{\omega}_{ijt} + g_{ij}}{2} \tag{9}$$

The index υ_{ijt} is asymmetric and ranges from zero to one. It is zero when firm i and firm j are both technologically and geographically "dissimilar", while it is unity if the closeness of the pair (i, j) is unity in both dimensions (technology and geography). It is worth emphasising that the assumption behind the Eq. (9) is that the weights for both indexes are equal.[9] All the weighting systems have been used to determine the stock of R&D spillovers [$Spill_{it}$ in Eq. (1)]. For the ith firm, the variable Spill_{it} is given by:

$$Spill_{it} = \sum_{\substack{j=1 \\ j \neq i}}^{N} \upsilon_{ijt} CT_{jt} \quad \text{with } i = 1, 2, \ldots, N \tag{10}$$

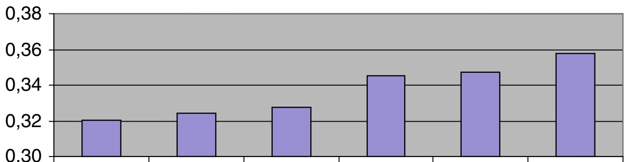
[9] The assumption made in Eq. (9) has been imposed by the fact that we have no prior information concerning the relative importance of technological similarity with respect to geographical proximity in the diffusion of knowledge. Hence the results we obtain using Eq. (9) must be used with caution and considered only a first step in a promising line of research. A natural extension of our study could be the estimation of the translog production function by including as regressors two distinct measures of R&D spillovers (the ones obtained using the technological similarity and the geographical distance) instead of the one that combines the weights. Although this is a fashionable idea, it can not be implemented within our framework of analysis because we use a system of equations and, thus, we have the constraint to identify the cost share equation (Eqs. 2–5). In other words, if we used two measures of R&D spillovers, then, we would include, in the system of equations, the cost share equations of R&D spillovers. This is a hard task, because the costs of R&D spillovers are not observable.

where υ_{ijt} indicates a generic weighting system as expressed in Eqs. (6)–(9) and CT_jt is the R&D stock of capital of the jth firm. We construct four stocks of R&D spillovers. Firstly, we refer to the stock of R&D spillovers obtained considering the symmetric similarity approach ($\upsilon_{ijt} = \omega_{ijt}$). Secondly, we compute the R&D spillovers using the asymmetric similarity index ($\upsilon_{ijt} = \hat{\omega}_{ijt}$). Thirdly, we calculate the flows of innovation through the index of geographical proximity ($\upsilon_{ijt} = g_{ij}$). Finally, we refer to the average of geographical and technological distance ($\upsilon_{ijt} = v_{ijt}$).

4 Data

In the empirical analysis, we use a firm-level dataset extracted from the eighth and ninth "Indagine sulle imprese manifatturiere" ("Survey of manufacturing companies") (IMM) surveys made by Capitalia (2002, 2005). These two surveys cover the period 1998–2003, contain standard balance sheets and collect a great deal of qualitative information from a large sample of Italian firms. Each survey considers more than 4,500 firms, including all Italian manufacturing firms with more than 500 workers and a representative sub-sample of firms with more than 10 workers (stratification used by Capitalia considers location, size and sector of the firm). After data cleaning we obtain a panel of 7,218 observations, with large N (1,203 cross sections) and small T (6 years).

We split the sample into R&D and non-R&D performing firms. The first group is composed of firms with positive R&D investments. Data in Fig. 1 indicate the dynamics of the number of R&D performers over the period 1998–2003. In 1998, there were 385, that is 32% of the entire sample of firms we consider, whereas this proportion was 36%, (430 firms) in 2003. Table 1 shows a breakdown of the sample of firms in 2003.[10] Regarding the geographical location, in 2003 about two-thirds of firms were located in northern Italy (445 in the North West and 382 in the North East). At the industry level, the full sample is dominated by firms in base metals, non-electrical machinery and textiles industries, while the petroleum refinery industry is represented by 6 firms only. In the case of R&D performers, most firms are located in northern Italy (177 out of 430 entities) and the industries with the highest number of companies are the non-electrical (102 firms) and the electrical machinery (61 firms) sectors. Finally, the distribution of firms by size is strictly in line with that of the entire Italian industrial system, which is characterized by the massive presence of small and medium sized firms (Table 1).



	1998	1999	2000	2001	2002	2003
Share	0,32	0,32	0,33	0,34	0,35	0,36

Fig. 1 Proportion of R&D performing firms in the full sample for each year from 1998 to 2003

[10] We limit the description of the sample to 2003 because the distributions of Italian firms by size, sector and over the period 1998–2002 are similar to those of 2003 (data are available upon request).

Table 1 Italian manufacturing firms by area, industry and size in 2003

Sector	Total sample					R&D performing firms				
	11–20 E	21–50 E	51–250 E	>250 E	Total	11–20 E	21–50 E	51–250 E	>250 E	Total
Food, beverages and tobacco	45	42	13	3	103	8	11	4	2	25
Textiles and apparel	54	51	30	13	148	17	15	12	7	51
Leather	20	16	14	0	50	3	3	9	0	15
Wood products and furniture	13	23	10	1	47	1	3	5	1	10
Paper, paper prod. and printing	35	20	10	3	68	4	5	1	0	10
Petroleum refineries and product	4	2	0	0	6	0	1	0	0	1
Chemicals	27	15	10	3	55	12	6	8	3	29
Rubber and plastic products	21	27	13	4	65	4	10	9	4	27
Non-metallic mineral products	33	32	11	5	81	9	3	6	1	19
Basic metal and fab. met. prod.	84	72	31	6	193	11	16	10	5	42
Non-electrical machinery	43	60	56	15	174	12	34	43	13	102
Electrical machinery and electronics	27	42	21	10	100	11	22	19	9	61
Motor vehicles and other transport equipment	9	8	5	5	27	2	2	2	4	10
Other manufacturing industries	37	30	18	1	86	9	8	10	1	28
Area										
North West	178	136	98	33	445	44	46	62	25	177
North East	142	139	79	22	382	36	47	51	19	153
Centre	89	91	37	10	227	15	28	17	4	64
South	43	74	28	4	149	8	18	8	2	36
Total	452	440	242	69	1, 203	103	139	138	50	430

Source: Our calculation from data by Capitalia (2005)

E = Employees

Table 2 reports the labour productivity and the physical and technological capital intensities. Labour productivity is expressed as value added to employees, whereas both capital intensities are computed with respect to value added. Data are expressed at 2000 real prices and refer to 2003.[11] Results reveal that labour productivity is 67,000 euros for the entire sample of firms, which is a higher value than that (63,000 euros) observed for R&D performers. This discrepancy depends on the productivity in the Centre (90,000 euros) and in the South (68,000 euros) of Italy. Moreover, these figures are driven by the high level of productivity of one firm with 21–50 workers operating in the petroleum industry and by two firms with more than 250 workers belonging to the paper sector. If we exclude these firms the differences in labour productivity decrease.

The comparison of results obtained when classifying firms by size and sectors indicates that in many cases the productivity of small and medium sized R&D performers is higher than the average production of the entire sample.[12] Such evidence seems to suggest that the small and medium sized R&D performers obtain a high level of productivity because they compensate for the diseconomies of scale by exploiting the advantages of being innovative.

As for physical capital intensity, we find that it is 1.31 for the total sample of firms and 1.27 for the R&D performers. What clearly emerges is that firms located in the South of Italy of a size of up to 250 workers have a physical capital intensity which is much higher than that observed for firms in the other areas. We find a confirmation of the overcapitalization of southern firms which the literature ascribes to the Italian policies addressed at helping the poorest areas of the country by making grants aimed at factor accumulation.

Bearing in mind the specific aim of this paper, the analysis of R&D capital intensity is of great interest. At a national level, it is 0.33 for all the R&D performing firms; moreover firms operating in North West of Italy register a value (0.42) which is higher than the national average, while in the other areas the R&D intensity is low (0.36 in the North East, 0.22 in the Centre and 0.05 in the South). The R&D intensity strongly differs when one considers firm size: it is 0.38 in the case of the firms with more than 250 employees, 0.33 for small firms (11–50 workers) and 0.2 for medium ones (51–250 employees). Finally, intensity is high in the chemical (0.82), electrical (0.54) and non-electrical (0.37) sectors and low in the wood (0.04) and paper (0.05) industries. These findings show that innovative activities are concentrated in the northern regions of the country, whose local industrial system is dominated by the presence of large and very innovative firms. They are further evidence supporting the map of innovative activity in Italy (see, among many others, Breschi and Lissoni 2001).[13]

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[11] Weights are given by $f_{it} = F_{it} \Big/ \sum_{t=1998}^{2003} \sum_{i=1}^{N} F_{it}$ where F_{it} is the sales of the ith firm at time $t (t = 1998, \ldots, 2003)$ belonging to a group sized $N (i = 1, \ldots, N)$.

[12] This holds, for example, in the case of the small (11–20 workers) and/or medium (21–50 workers) firms active in the food, textiles, paper, rubber, electrical, non metallic, non electrical and motor vehicles sectors.

[13] The high level of R&D capital intensity in the same regions of the country and in specific sectors finds an explanation in the high concentration of R&D investments. Indeed, 5% of the sample, that is 28 firms, accounted for 71% of total R&D investments in 2003. This 5% of firms invests, on average, more than five million euro per year and is geographically very concentrated (25 out of 28 firms are located in northern Italy). Again, 20% of the sample is composed of 111 firms and accounts for 89% of R&D investments (for ease of exposition, data are available on request only).

Table 2 Labour productivity and factor intensity in Italian manufacturing firms by industry, area and size in 2003 (weighted average)

Sector	Total sample									
	Y/L					K/Y				
	11–20 E	21–50 E	51–250 E	>250 E	Total	11–20 E	21–50 E	51–250 E	>250 E	Total
Food, beverages and tobacco	43	54	43	61	53	3.37	2.50	1.19	4.45	3.12
Textiles and apparel	52	49	41	61	55	0.69	0.97	1.33	1.28	1.19
Leather	40	38	43	–	41	0.68	0.58	1.36	–	1.09
Wood products and furniture	34	43	37	72	44	0.86	1.76	1.26	1.46	1.43
Paper, paper prod. and printing	40	56	50	183	147	0.90	0.89	1.25	0.73	0.82
Petroleum refineries and product	74	260	–	–	229	1.32	1.92	–	–	1.82
Chemicals	69	78	67	74	73	1.09	1.40	1.30	0.59	0.83
Rubber and plastic products	49	45	60	81	67	0.95	1.19	2.79	1.62	1.79
Non-metallic mineral products	60	53	51	85	72	1.67	1.99	2.10	1.56	1.72
Basic metal and fab. met. prod.	63	46	73	60	62	1.23	1.34	1.21	1.74	1.36
Non-electrical machinery	49	56	64	65	63	0.57	0.55	0.76	0.90	0.80
Electrical machinery and electronics	40	44	59	51	51	0.63	0.56	0.67	1.02	0.85
Motor vehicles and other transport equipment	39	42	35	58	55	0.71	0.87	0.99	1.56	1.48
Other manufacturing industries	47	36	40	38	40	0.79	0.85	1.05	0.78	0.91
Area										
North West	54	50	57	66	61	0.95	1.31	1.07	1.18	1.14
North East	48	53	54	72	62	1.02	1.08	0.92	1.82	1.40
Centre	58	50	60	120	90	1.03	0.87	1.30	1.05	1.06
South	40	88	50	69	68	3.28	1.96	2.82	1.47	2.12
Total	52	58	55	79	67	1.27	1.27	1.18	1.38	1.31

Table 2 continued

Sector	R&D performing firms														
	Y/L					K/Y					CT/Y				
	11–20 E	21–50 E	51–250 E	>250 E	Total	11–20 E	21–50 E	51–250 E	>250 E	Total	11–20 E	21–50 E	51–250 E	>250 E	Total
Food, beverages and tobacco	49	62	49	57	56	1.60	2.23	1.11	4.68	3.60	0.16	0.07	0.12	0.10	0.10
Textiles and apparel	49	52	42	68	62	0.82	1.00	1.22	1.10	1.09	0.40	0.27	0.27	0.07	0.14
Leather	45	38	47	–	46	0.62	0.59	1.51	1.01	1.40	0.28	0.23	0.07	0.01	0.09
Wood products and furniture	32	48	40	79	51	0.89	1.22	1.38	–	1.24	0.11	0.07	0.03	–	0.04
Paper, paper prod. and printing	51	57	60	195	133	0.69	0.72	1.64	0.51	0.82	0.14	0.07	0.09	0.01	0.05
Petroleum refineries and product	53	98	–	–	85	1.17	0.51	–	–	0.69	0.04	0.18	–	–	0.14
Chemicals	61	110	68	74	74	1.12	1.01	1.37	0.59	0.75	0.66	0.81	0.31	0.94	0.82
Rubber and plastic products	70	54	60	81	73	1.10	1.37	1.74	1.62	1.61	0.39	0.17	0.33	0.41	0.37
Non-metallic mineral products	41	60	52	78	71	1.13	1.75	1.48	1.38	1.41	0.14	0.19	0.14	0.08	0.10
Basic metal and fab. met. prod.	48	42	47	62	55	1.10	1.14	1.51	1.32	1.34	0.17	0.09	0.17	0.52	0.35
Non-electrical machinery	58	59	66	63	64	0.50	0.55	0.77	0.88	0.81	0.34	0.32	0.22	0.48	0.37
Electrical machinery and electronics	46	47	58	49	51	0.77	0.47	0.67	1.03	0.87	0.24	0.27	0.43	0.65	0.54
Motor vehicles and other transport equipment	46	35	36	61	59	1.13	2.27	0.95	1.30	1.29	0.09	0.06	0.26	0.23	0.23
Other manufacturing industries	81	39	41	38	43	0.48	0.95	1.16	0.78	0.97	0.15	0.17	0.16	0.28	0.19
Area															
North West	52	53	60	65	62	0.90	1.13	1.06	1.09	1.08	0.27	0.40	0.28	0.49	0.42
North East	56	63	48	68	63	0.82	0.53	0.96	1.86	1.52	0.27	0.23	0.17	0.36	0.30
Centre	58	55	69	65	64	0.82	0.98	1.38	1.11	1.15	0.54	0.18	0.18	0.22	0.22
South	39	43	53	75	66	1.47	2.49	1.61	1.02	1.32	0.21	0.07	0.29	0.05	0.10
Total	53	56	56	67	63	0.91	1.00	1.09	1.40	1.27	0.33	0.25	0.23	0.38	0.33

Source: See Table 1. Weights are expressed as the sales of the ith firm in relation to the aggregate sales of the group

Y/L value added/employee (in .000 of Euro), K/Y physical capital/value added, CT/Y technological capital/value added, E = Employees

5 Results

5.1 Output elasticities

Although the individual coefficients of the regressors in the translog production function are not directly interpretable, the 3SLS estimates merit a very brief comment. From data reported in Appendix A, it emerges that the majority of the interactive terms and the squared variables of the translog is significant. This means that if we used a Cobb–Douglas production function, we would introduce a bias in the estimations due to the omission of relevant variables.

We focus the discussion on the output elasticity retrieved from the estimates of the translog production. Data reported in column 1 of Table 3 show the outcomes that we obtain using the symmetric index of technological similarity, while, in columns 2, 3 and 4, we present the findings associated to the other weighting systems (the asymmetric index of technological similarity, the index of geographical proximity and their average, respectively). We expect that the method of weighting the flow of innovation matters in determining the impact of R&D spillovers on firms' output.

The first finding is that all the output elasticities are positive and highly significant. With regards labour, we find that the elasticity varies around 0.39, except when we use the asymmetric index of similarity. In this case, it is 0.49. The same behaviour is found for elasticity with respect to physical capital (0.23 in column 2) and R&D capital (0.14). Finally, the magnitude of the impact of R&D spillovers on the level of firm production is high: the elasticity is roughly 0.3, but it is as low as 0.14 when the flow of innovation is weighted through the pure asymmetric index of technological similarity

Table 3 Output elasticity in Italian R&D performing firms

Output elasticity	Italy			
	Symmetric techn. Spill. $\upsilon_{ij} = \omega_{ij}$	Asymmetric techn. Spill. $\upsilon_{ij} = \tilde{\omega}_{ij}$	Geograph. Spill $\upsilon_{ij} = g_{ij}$	Asymm. techn. and geogr. Spill. $\upsilon_{ij} = \nu_{ij}$
L	0.4175***	0.4873***	0.3718***	0.3763***
	(0.004)	(0.00347)	(0.00471)	(0.00462)
K	0.1986***	0.2324***	0.1693***	0.1716***
	(0.00315)	(0.00272)	(0.00366)	(0.00358)
CT	0.1120***	0.1438***	0.1063***	0.1045***
	(0.00205)	(0.00177)	(0.00251)	(0.0024)
Spill	0.2718***	0.1364***	0.3526***	0.3476***
	(0.00805)	(0.00639)	(0.0099)	(0.00964)

3SLS estimations (1998–2003)

Note: Standard errors reported in brackets

*** Statistical significance at 1% level (column 2, Table 3).[14] These outcomes confirm the hypothesis that elasticities vary according to the procedure used to weight technology flows. More specifically, there are substantial differences in results when considering the two preferred methods of weighting (the asymmetric technological and the geographical indexes). Without considering geography, from regressions run using the asymmetric index of technological similarity, we find that the elasticity of external technology is 0.13 and that the major contribution to production comes from factors under the direct control of the firm (labour, physical and own R&D capital). It is clear that this system is generally better than that one obtained using the symmetric index of similarity. However, the flow of innovation across firms is not determined only by technological similarity, but also depends on geographical proximity. This is particularly true in Italy, where localised knowledge spillovers (Breschi and Lissoni 2001) play a key role in technology transmission in many areas of the country characterised by the presence of agglomerations of small and medium sized firms that are similar and highly connected (the so called *Italian industrial districts*). Social interaction in these areas (Guiso and Schivardi 2007) creates the local conditions which foster the circulation of knowledge, in line with the evidence provided by Jaffe et al. (1993). In our perspective, the estimated output elasticity (0.35) of R&D spillovers obtained using the spatial proximity (Table 3, column 3) stresses the role of geography as a vehicle for enhancing the transmission of technology and the firm's performance. These results are robust according to the evidence which one obtains by sub-aggregating the firms according to their location (Table 4). Indeed, the impact of R&D spillovers on production is always higher in regressions using geographical proximity than in regressions based on the asymmetric technological similarity, whatever the area of the country (North West, North East and Centre-South). However, analysis carried out area-by-area highlights some differences. Focusing on R&D capital and R&D spillovers and looking at regressions using asymmetric technological proximity, we find that the elasticity of R&D capital slightly differs area-by-area (it ranges from 0.138 to 0.158). On the other hand, external technology exerts a marginal effect on production in the Centre and in the South of Italy compared to that estimated for the North of the country: R&D spillover elasticity is high in the northern regions (0.17 in the North-West and 0.14 in the North East) and very low (0.09) in the Centre-South of the country. Whatever the distance between firms, this result is in line with the evidence according to which, in the Centre-South of the country, innovative efforts are low and the local industrial systems are comprised of strongly dissimilar companies, i.e., in terms of human capital, market and product orientation, technology. Such peculiarities reduce firms' capacity to absorb external knowledge and, as a consequence, the role of R&D spillovers is found to be limited.

Previous findings are subject to criticism, because firms' exposure to R&D spillovers relies on technological similarity or on geographical proximity, only. Disregarding a channel (similarity or proximity) through which technology spills over from one

[14] A high spillover elasticity, about 0, 60, is also obtained by Cincera (2005) and Los and Verspagen (2000). The sample analyzed by Cincera (2005) is composed of large firms and the period considered is 1987–1994. Los and Verspagen (2000) use a panel of USA manufacturing firms from 1977 to 1991. In both papers, the weighting system is the uncentered correlation calculated considering patent data and the production function is the Cobb–Douglas.

Table 4 Output elasticity in Italian manufacturing firms by area. 3SLS estimations (1998–2003)

Output elasticity	North-West			North-East			Centre-South		
	Asymmetric techn. Spill.	Geograph. Spill	Asymm. techn. and geogr. Spill.	Asymmetric techn. Spill.	Geograph. Spill	Asymm. techn. and geogr. Spill.	Asymmetric techn. Spill.	Geograph. Spill	Asymm. techn. and geogr. Spill.
	$\upsilon_{ij} = \tilde{\omega}_{ij}$	$\upsilon_{ij} = g_{ij}$	$\upsilon_{ij} = \nu_{ij}$	$\upsilon_{ij} = \tilde{\omega}_{ij}$	$\upsilon_{ij} = g_{ij}$	$\upsilon_{ij} = \nu_{ij}$	$\upsilon_{ij} = \tilde{\omega}_{ij}$	$\upsilon_{ij} = g_{ij}$	$\upsilon_{ij} = \nu_{ij}$
L	0.4793***	0.4227***	0.4252***	0.4880***	0.3838***	0.3849***	0.4975***	0.3467***	0.3490***
	(0.00582)	(0.00691)	(0.00693)	(0.0055)	(0.00713)	(0.0073)	(0.00717)	(0.01068)	(0.01041)
K	0.2106***	0.1716***	0.1713***	0.2119***	0.1551***	0.1536***	0.2620***	0.1714***	0.1731***
	(0.00444)	(0.00557)	(0.0053)	(0.00397)	(0.006)	(0.00587)	(0.00523)	(0.00811)	(0.00792)
CT	0.1383***	0.1235***	0.1211***	0.1581***	0.1199***	0.1163***	0.1406***	0.0832***	0.0817***
	(0.00324)	(0.00407)	(0.00392)	(0.00288)	(0.00433)	(0.00423)	(0.00309)	(0.00514)	(0.00493)
Spill	0.1719***	0.2823***	0.2824***	0.1419***	0.3412***	0.3453***	0.0998***	0.3987	0.3961***
	(0.01145)	(0.01408)	(0.01394)	(0.00975)	(0.01437)	(0.01436)	(0.01412)	(0.0226)	(0.02193)

Note: Standard errors reported in brackets

*** Statistical significance at 1% level firm to another is a severe shortcoming of the analysis. We attempt to overcome this caveat by averaging the indeces of technological similarity and geographical proximity (see Eq. 9 and note 9). The estimates for the entire sample of firms indicate that the output elasticity of the internal R&D capital is 0.1, while that of external technology, namely the impact on production of R&D spillovers, is 0.34 (Table 3). We find clear evidence that the production of the Italian manufacturing sector is strongly dependent on the technology that firms absorb from other firms. This finding also holds when the level of aggregation is at sub-national level. In fact, the highest value (0.39) for the elasticity of technological spillovers has been estimated for firms located in the Centre-South of Italy, while, in the other regions, the elasticity is 0.34 in the North-East and 0.28 in the North-West. From one region to another, we also observe different results for the elasticity of internal R&D capital, which varies from 0.12 in the North West to 0.08 in the Centre-South (Table 4). Thus, in order to perform well, firms in the central and southern Italian regions (i) use R&D spillovers to compensate for the low level of internal innovative efforts and (ii) are able to gain great advantages from external technology.

In order to better understand the relationships between factors, the next sub-paragraph highlights the estimates of the elasticity of substitution proposed by Morishima (1967).

5.2 Elasticity of substitution

This section focuses on the degree of substitutability/complementary among inputs. This is done by considering the elasticity of substitution proposed by Morishima (1967), which is a precise measurement of how the s, k input ratio responds to a change in the kth price (Celikkol and Stefanou 1999). Given this definition it follows that (a) two inputs are substitutes (complements) when the Morishima elasticity is positive (negative) and (b) Morishima elasticity of substitution is not symmetric.

Table 5 shows the results of the estimated elasticities of substitution obtained when the flow of R&D capital is weighted by using the method that combines firms' technological similarity and geographical proximity (cfr Eq. 9). For any pair of inputs, we report the estimated value of elasticity, its standard error and the t-statistics used to test the null hypothesis that the elasticity is unity.

The first outcome to be emphasized is that almost all elasticities are significantly different from unity.[15] This evidence supports our choice to use the translog instead of the Cobb–Douglas specification which, on the contrary, assumes elasticity to be unity. Moreover, it is worth noticing that labour and physical capital and labour and R&D spillovers are Morishima substitutes, while R&D capital and R&D spillovers are Morishima complements, whatever the change in price. As for the other pairs of inputs, because of asymmetry of the Morishima index, the sign of the relationship depends on which price changes. Again, we find evidence of complementarity of internal R&D

[15] The hypothesis that Morishima elasticity is unity is always rejected when analysing the entire sample of firms and the sub-sample of firms localized in the Centre-South of Italy, while it is not rejected in three cases in the North-West (R&D capital and R&D spillovers, R&D capital and labour, physical capital and R&D capital) and in one case in the North East of Italy (R&D capital and labour) (Table 5).

Table 5 Morishima elasticity of substitution by geographical areas (as a mean average of the sample) over the period 1998–2003

	Morishima elasticity of substitution			
	Italy	North West	North East	Centre-South
Sp and L	0.667***	1.094***	1.179***	0.457***
	(0.019)	(0.0212)	(0.026069)	(0.046)
	−(17.3536)	(4.4195)	(6.8767)	−(11.8009)
Sp and K	0.050	0.481***	0.252**	−0.262***
	(0.051)	(0.0696)	(0.104284)	(0.0999)
	−(18.5856)	−(7.4592)	−(7.1762)	−(12.634)
Sp and CT	−2.596***	−0.809**	−0.382	−6.767***
	(0.3028)	(0.3796)	(0.6436)	(1.0884)
	−(11.8776)	−(4.7653)	−(2.1472)	−(7.1364)
L and Sp	0.526***	1.074***	1.055***	0.223***
	(0.0317)	(0.0128)	(0.0136)	(0.0814)
	−(14.935)	(5.8064)	(4.0263)	−(9.5467)
K and Sp	−0.319***	0.557***	−0.224	−0.850***
	(0.1015)	(0.09809)	(0.13802)	(0.23589)
	−(12.9949)	−(4.5201)	−(8.8686)	−(7.844)
CT and Sp	−7.614***	0.116	−1.681**	−22.303***
	(0.7322)	(0.5083)	(0.7934)	(2.5931)
	−(11.7655)	−(1.739)	−(3.3793)	−(8.9866)
CT and L	3.619***	0.720	1.607*	9.157***
	(0.4563)	(0.5316)	(0.8669)	(1.5381)
	(5.7405)	−(0.5266)	(0.7001)	(5.3032)
CT and K	2.116***	−0.071	1.123*	6.574***
	(0.331)	(0.3597)	(0.6346)	(1.1064)
	(3.3729)	−(2.9774)	(0.1941)	(5.0383)
L and CT	−2.521***	−0.811**	−0.366	−6.629***
	(0.2992)	(0.3817)	(0.6459)	(1.0827)
	−(11.768)	−(4.7443)	−(2.1148)	−(7.046)
K and CT	−2.391**	−0.870**	−0.295	−6.387***
	(0.3016)	(0.3878)	(0.6567)	(1.0766)
	−(11.2423)	−(4.8227)	−(1.9726)	−(6.8616)
L and K	0.116**	0.502***	0.360***	−0.166*
	(0.0488)	(0.0739)	(0.1106)	(0.0859)
	−(18.1116)	−(6.7374)	−(5.7835)	−(13.5749)
K and L	0.831***	1.079***	1.568***	0.666***
	(0.0561)	(0.0949)	(0.1292)	(0.1141)
	−(3.0183)	(0.8305)	(4.3994)	−(2.9295)

Data refers to the results obtained using Eq. 9 as weighting system of R&D spillovers

Note: Standard errors reported in brackets. The second row of standard errors refers to the t-test $H_0 : \sigma_{ij} = 1$

*, **, *** Statistical significance at the 10, 5 and 1% level, respectively

capital with respect to all other inputs $(K, L, Spill)$ when we consider a change in the of internal technology. This means that a decrease in internal R&D capital price induces an increase in the relative use of other inputs. Table 5 reveals that the sign of Morishima elasticity does not vary when the analysis is carried out at sub-national level. The only two exceptions are the positive sign, although not significant, of the Morishima index between internal and external R&D capital in the North-West of Italy and the negative sign related to the input ratio between R&D spillovers and physical capital in the Centre-South of the country. However, several differences emerge when looking at the magnitude of the Morishima elasticity of substitution estimated for the three macro-areas we analyse. We find that the sample of firms located in the Central-Southern regions show a higher value of the elasticity between internal and external R&D capital than that estimated in the other areas. In particular, the internal R&D capital/R&D spillover ratio in this area of the country is very sensitive to the price of R&D spillovers: a decrease of 1% in the price of R&D spillovers yields an increase of 22.3% in the input ratio. In terms of policy implications, these results indicate that policies resulting in lowering the price of R&D capital (both internal and external) would cause significant increase in the use of technology and ultimately an improvement in firms' performance. Given the estimated values of Morishima elasticity, the economic gains of such policies would be higher in the Centre-South than in the North of Italy. The low level of R&D intensity in Italy and, in particular, in the Centre and South of the country, allows the Italian government to easily implement public intervention in promoting R&D activities.

6 Conclusions

Compared to the existing empirical literature on the role of R&D spillovers at firm level, this paper provides two original contributions. The first deals with the functional form to be used in modelling the impact of R&D on production, whereas the second concerns the use of different measures of R&D spillovers.

As far as functional form is concerned, we use the translog production function, which is more flexible than the Cobb–Douglas. The results support our choice, because we reject the assumption inherent the technology of a Cobb–Douglas. It is worth noting that the literature to which this paper refers never uses the translog function and generally omits the testing of the suitability of the Cobb–Douglas specification.

With regards R&D spillovers, we consider and compare different measurement methods of external technology. This procedure helps to understand whether the role of R&D spillovers is sensitive to the method used to weight the flows of innovation across firms. To be precise, in order to determine the R&D spillovers stock we use a measure of similarity between firms. It is assumed that the greater the similarity between two firms in terms of size and R&D efforts, the more they will absorb each other's technology. To overcome the problem that the similarity index produces a symmetric weighting scheme, we consider an asymmetric transformation of the uncentered correlation. We also test the hypothesis that the closer two firms are, the more they will benefit from each other's R&D. This is done through a spatial weighting scheme based on the great circle distance between firms.

In the econometric section we control for selection bias by using the 2-steps IV estimator, where, in the first step, we model the selection model that leads the firms to invest, or not, in R&D. In the second step, we estimate the translog production function with the 3SLS method. Data are from Capitalia and refer to a balanced panel data of 1,203 manufacturing firms over the period 1998–2003.

The key result is that output elasticity with respect to R&D spillovers is always positive and significant. Moreover, we find that different measurement methods of spillovers bring about different effects of inputs on firm output. In fact, we show that geographical proximity is relevant in determining the final result: our regressions based only on the asymmetric index of technological similarity underestimate the impact of R&D spillovers. These regressions do not control for geographical distance and, thus, are less precise in measuring firms capacity to absorb technology. Finally, from a regional point of view, it emerges that the role of external technology is higher in the Centre and South of Italy than in the North of the country.

As for the elasticity of substitution among inputs, we find clear evidence that R&D spillovers are Morishima complements to the internal stock of R&D capital. A joint reading of this result and of that concerning the positive impact of R&D capital on firms' production advocates great public intervention aimed at encouraging the adoption and diffusion of technology in the Italian manufacturing sector.

Appendix A

Tables 6 and 7.

Table 6 Results on the probability of investing in R&D for Italian manufacturing firms

	Symmetric technol. Spill. $\upsilon_{ij} = \omega_{ij}$	Asymmetric technol. Spill. $\upsilon_{ij} = \tilde{\omega}_{ij}$	Geograph. Spill. $\upsilon_{ij} = g_{ij}$	Asymmetric technol. and geograph. Spill. $\upsilon_{ij} = \nu_{ij}$
ln(H)	0.0152 (0.003)***	−0.0181 (0.004)***	0.0226 (0.003)***	−0.0074 (0.003)**
ln(cf)	−0.0150 (0.03)	0.0481 (0.025)*	0.0635 (0.025)**	0.0405 (0.026)
D_exp	0.4117 (0.064)***	0.5198 (0.058)***	0.6043 (0.057)***	0.5727 (0.059)***
ln(ict)	0.1567 (0.025)***	0.1595 (0.022)***	0.1582 (0.021)***	0.1726 (0.022)***
North-West	−0.0578 (0.108)	−0.0097 (0.095)	−0.2835 (0.141)**	−1.2155 (0.132)***
North-East	0.1028 (0.106)	0.2037 (0.094)**	−0.1192 (0.138)	−0.9788 (0.127)***
Centre	0.1465 (0.116)	0.4111 (0.104)***	0.0162 (0.13)	−0.5712 (0.125)***
Scale	0.2264 (0.083)***	0.0297 (0.07)	0.0655 (0.068)	0.0408 (0.07)
Specialized	0.3112 (0.069)***	0.2959 (0.059)***	0.4272 (0.056)***	0.3462 (0.059)***
High-tech	0.4311 (0.167)***	0.5656 (0.132)***	0.7353 (0.126)***	0.6637 (0.14)***
ln(k)	−0.3515 (0.547)	0.3191 (0.176)*	−0.5131 (1.18)	0.6088 (1.138)
ln(l)	1.9218 (1.063)*	0.2596 (0.295)	−1.0138 (2.226)	−3.3991 (2.166)
ln(sp)	−28.0632 (1.25)***	−1.2979 (0.127)***	−7.3220 (5.588)	−50.1745 (4.37)***
ln(l)ln(k)	−0.0526 (0.032)	−0.0286 (0.03)	−0.0188 (0.026)	−0.0312 (0.03)
ln(l)ln(sp)	−0.1443 (0.084)*	0.0458 (0.021)**	0.1317 (0.165)	0.3131 (0.167)*

Table 6 continued

	Symmetric technol. Spill. $\upsilon_{ij} = \omega_{ij}$	Asymmetric technol. Spill. $\upsilon_{ij} = \tilde{\omega}_{ij}$	Geograph. Spill. $\upsilon_{ij} = g_{ij}$	Asymmetric technol. and geograph. Spill. $\upsilon_{ij} = \nu_{ij}$
ln(k)ln(sp)	0.0369 (0.043)	−0.0197 (0.012)	0.0424 (0.087)	−0.0434 (0.087)
$[\ln(l)]^2$	0.0845 (0.082)	−0.0794 (0.071)	−0.1017 (0.065)	−0.0609 (0.071)
$[\ln(k)]^2$	0.0155 (0.018)	−0.0055 (0.018)	−0.0022 (0.016)	0.0084 (0.018)
$[\ln(sp)]^2$	2.4954 (0.113)***	0.1658 (0.012)***	0.5373 (0.428)	4.0965 (0.34)***
	152.66 (7.187)***	1.65 (1.11)	44.74 (36.845)	304.42 (28.705)***
Wald test	3595	3595	3595	3595
p-value	910.25	909.38	772.67	860.07
Pseudo R^2	0.00	0.00	0.00	0.00

Probit estimates over the period 1998–2003

Note: Standard errors in brackets

H human capital, *cf* cash flow, *D_exp* dummy equal to one if the firm exports and zero otherwise, *ict* ICT investments, *k* physical capital, *l* labour, *sp* spillovers, sectoral (according to the Pavitt classification: traditional, scale, specialized and high technological industries) and territorial (North-West, North-East, Centre and South) dummies

***, **, * Statistical significance at 1, 5 and 10%, respectively

Table 7 Estimated coefficients of the translog production function for Italian manufacturing firms

	Symmetric technol. Spill. $\upsilon_{ij} = \omega_{ij}$	Asymmetric technol. Spill. $\upsilon_{ij} = \tilde{\omega}_{ij}$	Geographical Spill. $\upsilon_{ij} = g_{ij}$	Asymmetric technol. and geograph. Spill. $\upsilon_{ij} = \nu_{ij}$
α_{L}	0.9491 (0.0306)***	0.7183 (0.0167)***	0.9501 (0.0324)***	0.9231 (0.0317)***
α_{K}	0.4412 (0.0225)***	0.3084 (0.0124)***	0.4324 (0.0238)***	0.4244 (0.0231)***
α_{C}	0.2826 (0.015)***	0.2302 (0.0081)***	0.3020 (0.017)***	0.2945 (0.0161)***
α_{Sp}	−0.6729 (0.0593)***	−0.2569 (0.0294)***	−0.6844 (0.0644)***	−0.6419 (0.0624)***
β_{LK}	0.0044 (0.0019)**	−0.0030 (0.0016)*	0.0020 (0.0018)	0.0028 (0.0018)
β_{LC}	0.0088 (0.0013)***	0.0057 (0.0011)***	0.0076 (0.0013)***	0.0084 (0.0013)***
β_{KC}	0.0058 (0.001)***	0.0016 (0.0009)*	0.0058 (0.001)***	0.0059 (0.001)***
β_{LSp}	−0.0659 (0.0041)***	−0.0336 (0.0026)***	−0.0606 (0.004)***	−0.0614 (0.0041)***
β_{KSp}	−0.0425 (0.0031)***	−0.0238 (0.002)***	−0.0381 (0.003)***	−0.0395 (0.0031)***
β_{CS_p}	−0.0246 (0.002)***	−0.0157 (0.0013)***	−0.0239 (0.0021)***	−0.0248 (0.0021)***
β_{LL}	0.0527 (0.0029)***	0.0308 (0.0022)***	0.0510 (0.0028)***	0.0501 (0.0029)***
β_{KK}	0.0323 (0.0017)***	0.0252 (0.0015)***	0.0303 (0.0016)***	0.0307 (0.0017)***
β_{CC}	0.0101 (0.0009)***	0.0084 (0.0008)***	0.0105 (0.0009)***	0.0104 (0.0009)***
β_{SpSp}	0.133 (0.0085)***	0.0731 (0.0053)***	0.1225 (0.0083)***	0.1256 (0.0086)***
Scale	0.1213 (0.0362)***	0.0662 (0.036)*	0.1006 (0.0357)***	0.0927 (0.0358)***
Specialized	0.1865 (0.0277)***	0.0877 (0.0276)***	0.1904 (0.0273)***	0.1722 (0.0273)***
High-tech	0.198 (0.0472)***	0.0055 (0.047)	0.2156 (0.0466)***	0.1813 (0.0467)***
North-West	0.1151 (0.0486)**	−0.0180 (0.0483)	−0.0293 (0.048)	−0.0326 (0.0482)
North-East	0.1603 (0.0486)***	0.1170 (0.0481)**	−0.0028 (0.0481)	0.0135 (0.0483)

Table 7 continued

	Symmetric technol. Spill. $\upsilon_{ij} = \omega_{ij}$	Asymmetric technol. Spill. $\upsilon_{ij} = \tilde{\omega}_{ij}$	Geographical Spill. $\upsilon_{ij} = g_{ij}$	Asymmetric technol. and geograph. Spill. $\upsilon_{ij} = \nu_{ij}$
South	0.0979 (0.0523)*	0.1249 (0.0518)**	−0.0454 (0.0517)	−0.0205 (0.0519)
Obs.	1,537	1,537	1,537	1,537
F-test	10,288.9	8,080.4	51,791.5	55,419.9
Prob > F	0.00	0.00	0.00	0.00
R-squared	0.83	0.85	0.84	0.83

Estimation Method: 3SLS (1998–2003)

Note: Standard errors reported in brackets

*, **, *** Statistical significance at the 10, 5 and 1 level, respectively. The instrumental variables considered are the 1-year lagged values of the endogenous variables

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